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Does Experience Matter? Innovations and the Productivity of ICT in German Services

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Non–technical summary

In spite of emerging disillusions about a 'New Economy', productivity effects of information and communication technologies (ICT) continue to play a key role in assessing the prospects and growth potentials of both firms and whole economies. In fact, the economic downturn currently experienced by some countries shows that ICT are far from being a panacea that yields permanent growth and the end of business cycles, as some analysts suggested at the peak of the hype. Rather, there is growing support for the view that it is the specific economic and strategic circumstances within the individual firm that determine the success of using the new technologies.

Recent studies have indicated that ICT investment in businesses is closely linked with complementary organizational changes and innovations since the use of ICT enables firms to restructure their internal organization and to re–engineer business processes. In this study, it is argued that firms with innovative experience are particularly well prepared to make productive use of ICT by introducing appropriate complementary innovations. Administrations of firms that have introduced innovations in the past are expected to be better prepared to assess the potentials and limits of introducing major changes, they may be more successful in training and motivating their employees to take part actively in the subsequent innovations and they may have acquired some degree of innovative reputation in new business areas which facilitates the sale of new products and services.

The corresponding empirical analysis is based on a representative data set for German service firms covering the period 1994–99. The results reveal significant productivity effects of ICT and entail strong support for the hypothesis that the experience gained from past innovations is a specific complement that makes ICT investment more productive. In particular, innovative experience significantly enhances the productivity of ICT whereas complementary innovations alone do not exhibit such an impact. Obviously, the productive implementation of ICT requires rather a long–term innovation strategy than some ad–hoc implementation. Moreover, the quantitative effects of process innovation experience on ICT productivity are bigger than experience gathered from past product innovations. Finally, the dependence on innovative experience is found to be a feature that distinguishes ICT from conventional (non–ICT) capital. Thus, the increasing importance of innovations may well be identified as a key characteristic of the so called 'New Economy'.

One implication of the findings of this study is that the fast technical progress and diffusion of ICT have contributed to a widening of productivity differentials between firms. Since it is widely argued that innovative activities are closely linked to the business environment and policy framework within countries, these differentials at the firm–level may have led to a further widening of the productivity gap between highly innovative economies and less dynamic regions.

Does Experience Matter? Innovations and the Productivity of Information and Communication Technologies in German Services

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Abstract

In this paper, it is argued that investment in information and communication technologies (ICT) are closely linked to complementary innovations and are most productive in firms with experience from earlier innovations. In the empirical analysis based on firm–level panel data covering the period 1994–99, system GMM estimates for an extended production function framework reveal significant productivity effects of ICT in the German service sector. Moreover, there is strong support for the hypothesis that experience gained from past process innovations makes ICT capital more productive but does not affect the productivity of other capital goods.

Keywords: Productivity, Information and Communication Technologies, Innovation, Services, Panel Data
JEL–Classification: C23, D24, L80, O32

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1 Introduction

In spite of emerging disillusions about a 'New Economy', productivity effects of information and communication technologies (ICT) continue to play a key role in assessing the prospects and growth potentials of both firms and whole economies. In fact, the economic downturn currently experienced by some countries shows that ICT are far from being a panacea that yields permanent growth and the end of business cycles, as some analysts suggested at the peak of the hype. Instead, there is growing support for the view that it is the specific economic circumstances that determine the success of using the new technologies. As emphasised by Bresnahan and Trajtenberg (1995) and Brynjolfsson and Hitt (2000), ICT serve primarily as 'enabling technologies' that require additional complementary innovation efforts to fully unfold their productivity potentials.

Various empirical studies support this view. In a macroeconomic study for nine OECD countries, Colecchia and Schreyer (2001) find that a rapid diffusion of ICT depends less on the existence of an ICT producing sector but rather on the flexibility of product and labour markets as well as the business environment. Reviewing a broad range of firm–level studies in both manufacturing and services, Brynjolfsson and Hitt (2000) point to the importance of management strategies and organisational changes for differing returns to ICT across firms. A study by Brynjolfsson et al. (2002) based on large U.S. firms listed at the stock markets reveals that computer–intensive firms focus strongly on innovative organisational forms. Moreover, firms that combine computer use with these organisational characteristics are valued disproportionately higher at the stock markets than firms that invest only in one of these dimensions. These findings are corroborated by Bresnahan et al. (2002) who find similar complementarities in production function estimations for a cross section of large U.S. firms. All these studies have an important message in common: in order to assess the impact of ICT it is crucial to investigate the firm–specific circumstances in which ICT are used.

The purpose of this paper is to shed more light on the factors that determine the success of productive ICT use. Unlike most previous studies of the topic, the approach envisaged in this study explicitly stresses the importance of ICT being part of the innovation process within a firm. Evolutionary approaches of innovation have emphasised the dynamic dimension of innovation due to learning effects. Innovation activities do not only help to create new knowledge but also to accumulate expertise that helps to exploit external knowledge (e.g., Cohen and Levinthal, 1989) and to facilitate subsequent own innovational activities either in a specific technological field (Stiglitz, 1987) or in terms of changes in organisational routines (Nelson and Winter, 1982; Dierickx and Cool, 1989). I argue that due to the enabling character of ICT applications, the success of ICT use depends on a firm's innovative history: if ICT use is productive only with complementary innovations, firms that have introduced innovations in the past will be better prepared for using ICT than firms without such innovation experience. Consequently, productivity effects of ICT are predicted to be higher in experienced firms.

Most previous empirical studies on the productivity effects of ICT have focussed on samples of large firms or firms from the manufacturing sector only. However, ICT investments are particularly pronounced in the service sector (OECD, 2000a). Moreover, business–related services have been the most important driver of economic growth over the last decades in the industrialised countries (OECD, 2000b). The empirical analysis in this paper therefore draws on panel data from a representative sample of more than 1200 German firms in business–related and distribution services for the period from 1994 to 1999. The econometric estimations are based on a system GMM estimator that allows to control for firm–level fixed effects, simultaneity of input and output decisions as well as measurement errors. The results indicate that innovative experience plays an important role for the productive usage of ICT but does not affect the productivity of conventional investments. These results are robust to the inclusion of variables that control for potential complementarities between innovations and skills of the workforce.

The paper is organised as follows. Section 2 presents the theoretical background and is followed by an overview on the employed data in section 3. Section 4 discusses the econometric issues and presents the empirical results for both a simple ICT–extended production function framework and the more specific model taking account of the role of innovative experience. Section 5 concludes with some comments on the implications of the findings.

2 Theoretical Background

The theoretical background is based on the synthesis of two main ideas. First, evidence from recent studies indicates that the productive use of ICT is closely linked to complementary innovations within firms. This link is hypothesised to be a special feature of ICT as opposed to other, more conventional types of capital. Second, it is argued that innovative capabilities are mainly firm–specific and must be accumulated over time. In the resulting model, both effects together lead to predicting a higher productivity of ICT within 'experienced' firms.

Deriving these hypotheses, the subsequent parts discuss innovational complementarities of ICT use, the dynamic aspects of innovative capabilities and some specifics of innovation in services. Finally, I present a production function framework that allows to assess the hypotheses empirically.

2.1 ICT and innovational complementarities

Apart from the broad and rapid diffusion of ICT, one of the most striking features of ICT is the wide scope of applications and of coinventions made possible by its use. These properties that distinguish ICT from most other capital goods have motivated researchers to designate ICT as a "General Purpose Technology" (GPT) and to compare it to other important inventions in the past such as electricity and the steam engine (David, 1990; Helpman, 1998; Rosenberg and Trajtenberg, 2001). As stressed by Bresnahan and Trajtenberg (1995), GPTs are essentially 'enabling technologies' that necessitate innovations in their application to become fully productive.

Innovational complementarities in application sectors are particularly widespread in the case of ICT. Various industries outside the ICT sector are using ICT components for own product and process innovations. For example, cars and domestic appliances are increasingly equipped with microcomputers that operate navigation systems and control operations of components. Similarly, service industries use cash machine tellers, online banking, e–commerce, and web–based after–sales support for new services and processes. Most importantly perhaps, ICT is used for improving the quality of existing products and services, in particular customer service, timeliness and convenience (Brynjolfsson and Hitt, 1995; Licht and Moch, 1999).

Moreover, ICT applications have great impacts also on processes and the organisation of work inside firms and administrations (Bresnahan and Greenstein, 1996). Firms employ more flexible and more easily programmable manufacturing tools that embody ICT (Milgrom and Roberts, 1990); supply chain management tools increasingly link the production processes of suppliers and clients; and new tools for customer care, such as customer relationship management, help to recognise changes in demand more quickly (Hammer, 1990; Rigby et al., 2002). In most cases, these developments involve substantial organisational changes that take time to be implemented and often entail new skill requirements for workers (Brynjolfsson and Hitt, 2000; Hempell, 2003).

The importance of complementary innovations in ICT using firms can hardly be underestimated. They are subject to high uncertainties and their costs typically exceed the direct investment costs of ICT (Bresnahan and

Greenstein, 1996). Moreover, as pointed out by Brynjolfsson et al. (2002) and Bresnahan et al. (2002), successful innovation associated to ICT use is very complex, involving simultaneous changes in various business areas.[1] Similarly, Milgrom and Roberts (1990; 1995) provide a model of complementarities and examples of how new technologies must be complemented by whole systems of innovations to achieve advances in productivity whereas isolated measures may even lower firm performance.

The fact that the productive use of ICT requires complex systems or 'clusters' of complementary innovations has two important implications. First, these clusters make imitation of successful ICT applications very difficult. Second, while specific technological know–how may be important for ICT use, expertise in organising and coordinating complementary systems of innovations in firms may be even more important. Firms that are familiar with organising complex internal changes thus have strong incentives to pursue competitive advantages through ICT–based innovations in spite of their inherent risks of failure. These aspects may help explain, for example, the ongoing success of firms such as DELL and Wal–Mart, where combining strong ICT investments with far–reaching innovations of business processes is associated to impressive productivity gains and business performance (Brynjolfsson et al., 2002).

The 'enabling' character of ICT also contrasts with most other types of capital. New vintages of conventional capital, such as machines, vehicles, or other equipment, are often faster, more reliable or more energy–efficient than old vintages and directly contribute to increasing productivity by rasing the speed of production or by reducing costs of materials. By contrast, computers and networks basically do nothing more than facilitating the exchange, processing and storage of information. To affect productivity, these characteristics must be exploited in through innovations in products, processes and the organisation of work. In this sense, technical progress is not fully embodied in ICT but requires complementary knowledge and innovation activities by its users. This is the main point of why strong complementarities with innovative experience are expected to be a feature that distinguishes ICT from other types of capital.

[1] Brynjolfsson et al. (1997) provide results from a case study of a large medical products producer, showing that investments in computer integrated manufacturing was associated to a whole list of innovations, including elimination of piece rates and a more frequent and richer interaction with customers and suppliers.

2.2 Innovative capabilities and the role of experience

Individual firms may differ in their capabilities to innovate. As maintained by Cohen (1995), two sort of capabilities are distinguished in the innovation literature. On the one hand, firms may be specialised in a particular technology or a related expertise which leads them to pursue different innovative activities. On the other hand, the ability to innovate is determined by organisational and procedural capabilities that condition the process of innovation. "In this view, firms are characterised as pursuing similar innovative activities, but some firms are more successful than others in either generating or profiting from innovation." (p. 203) [2]

Both aspects of capabilities, which I denote as *specialisation* and *organisation* capabilities for simplicity, can be interpreted either as the outcome of an exogenously given random process (e.g., Cohen and Klepper, 1992) or a dynamic process where learning from past innovations contributes to a stock of accumulated capabilities (e.g., Cohen and Levinthal, 1989). These dynamically accumulated capabilities to innovate are what I denote as 'innovative experience'. As set out in the following, both types of innovative capabilities — specialised and organisational ones — are sources of innovative experience, but have differing implications.

On the one hand, experience due to specialisation is linked to a certain technology. In their seminal paper to the theory of 'localised technological change', Atkinson and Stiglitz (1969) consider the fact that technological advances may have asymmetric effects on different technologies of production. They maintain that innovations that affect one technology, i.e. one way of producing a good, may have no or only limited effects on other technologies. In this framework, accumulation of experience in production due to learning–by–doing (Arrow, 1962) may be localised to a certain technology and give rise to specialisation benefits. As a consequence, a high localisation of learning in production implies that firms may be locked–in into a particular technology and have little incentives to switch to alternative technologies. As pointed out in Stiglitz (1987), this learning due to specialisation may not be confined to production (localised learning–by–doing) but may also extend to the process of innovation (localised learning to learn).

A related idea is contained in the concept of 'absorptive capabilities' put

[2] Considering product innovations in the electronics and the food–processing industry, von Tunzelmann (1998) investigates the dichotomy between advantages from technical specialisation on the one hand and increasing complexity, i.e. diversity of technologies required for product innovations, on the other. Based on industry studies, he finds that multi–technology companies try to reconcile the contradiction with greater specialisation in sub–units of the firm.

forward by Cohen and Levinthal (1989). They argue that innovation activities (and R&D in particular) do not only generate new information, but also enhance a firm's ability to identify, assimilate and exploit existing externally available knowledge. This ability is greatest in technological fields that are related to the stock of prior knowledge. Moreover, possessing related knowledge may also help to predict the nature and commercial potential of technological advances in a specific fields (Cohen and Levinthal, 1990). This helps to reduce the inherent risks of innovations in the specific field, but may also facilitate imitation of successful innovations introduced by technologically leading competitors if the underlying intellectual property can be protected only imperfectly.

Dynamic spillovers due to learning–by–doing and learning–to–learn imply that optimising firms will envisage non–myopic strategies. Firms will accept initial losses in new technologies if learning spillovers are sufficiently high to make profits subsequently. Moreover, non–convexities in production, for example due to high fixed costs, are exacerbated by these dynamic spillovers. These dynamics may be intensified by the sequential nature of innovations, i.e. when innovations are explicitly based on successful earlier innovations in the specific technological field. Mansfield (1968) and Stoneman (1983) argue that a firm's innovative success enhances its technological opportunities and thereby makes further success more likely. This 'success breeds success' hypothesis finds empirical support in a study by Flaig and Stadler (1994). They find that firms that have introduced innovations in the past are indeed more likely to innovate in subsequent years.

These effects of localised learning apply particularly well to product innovations in R&D–intensive industries, e.g. producers of ICT like microprocessors, memory items and software. Scientific knowledge plays a major role in these industries and absorptive capacities as a source of experience help firms to exploit knowledge from public institutions (such as universities) and competitors. Moreover, innovations in these industries are often sequential in the sense that solutions entailed in earlier innovations facilitate problem solving in current research. In the case of ICT producers, these intertemporal spillovers may be intensified additionally by network externalities and the ability to set standards (see e.g. David, 1987).

In contrast to localised learning, innovative experience based on accumulated *organisational* capabilities reflects the more general flexibility to adapt to new economic environments. The dynamics of the organisational dimension have received major attention in evolutionary approaches of innovations. Nelson and Winter (1982) point out that apart from the skills of the individual workers, processes of organisational learning play a major role for a firm's capabilities to innovate. They argue that firms (like other organisations) act in 'routines' as patterns of regular and predictable behaviour. These patterns do not only apply to specific production techniques but also to higher–order decision rules and patterns of innovative activities. Much of an organisation's knowledge is tacit and firm–specific and must be acquired over time. Inspired by Nelson and Winter's approach, Cohen and Levinthal (1990) suggest that innovations in organisations have to resort to some degree of diversity of knowledge within firms. They highlight that even though learning of individuals is highest when the object of learning is related to what is already known, a firm's absorptive capacity it not simply the sum of the absorptive capacities of its employees but equally depends on the transfer and coordination of knowledge across and within subunits. More diverse knowledge structures will enhance the firm's capacity for making novel linkages and associations beyond what specialised individuals can achieve. This aspect of ingenuity in innovations seems particularly important in the context of clusters of innovations associated to the use of ICT as discussed above.

The organisational aspect of innovative capabilities and their dynamics have also received major attention in the management literature. Various exponents of 'resource–based' approaches to the firm have highlighted accumulated intangible assets and core competencies as explanations for sustained competitive advantages of individual firms (see, e.g., Wernerfelt, 1984). To become a source of sustained competitive advantages, these resources and capabilities must be valuable, rare, imperfectly imitable and not substitutable (Barney, 1991). Similarly, intangible resources have been identified as main determinants for ability of firms to conduct R&D (Galende and de la Fuente, 2003).

Complementing this resource–based view, the 'dynamic capability approach' emphasises the dynamic nature of firm–specific resources (Teece et al., 1997). Dierickx and Cool (1989) provide a model of intangible assets that are accumulated internally and that form the basis of competitive advantages due to *Asset mass efficiencies* and *time compression diseconomies*. *Asset mass efficiencies* mean that the more accumulated assets a firm has, the lower are the marginal costs of increasing the stock further. *Time compression diseconomies* imply that the marginal costs of investments in intangibles in a given period increase more than proportionally, such that asset accumulation cannot be rushed.[3] Both these features prevent competitors with a smaller stock of relevant intangibles from imitating the production

[3]This idea corresponds to strictly convex adjustment costs in investment theory.

technology by catching up. Moreover, if there are complementarities between different types of asset stocks, combinations of these assets are even more difficult to be replicated by imitators. As exemplified by Dierickx and Cool (1989), if product and process innovations originate in customer request or suggestions, it may be particularly difficult to develop technological know–how for firms that do not dispose of an own extensive service network.[4]

These aspects of sustained differences between firms suggest that the organisational dimension of innovative experience is particularly important in the innovative process of making *use* of ICT. As pointed out in the previous section, the general purpose character of ICT implies that using these technologies is most successfully complemented by clusters of innovations and that firms may vary in their capability to co–ordinate these innovations. The considerations from evolutionary and dynamic capability theories suggest that firms must acquire this capability internally over time and that experience collected in the course of earlier innovations is important for this process. Unlike the localised nature of innovative experience that is necessary for advances in the innovation of particular technologies (such as ICT production), the character of experience relevant for the manifold innovations based on ICT *use* will be confined less to a particular or 'localised' technological field but will consist in organisational experience resulting from diversity of expertise and the ability to combine and exploit this expertise. In the following section, I set out that this view may be particularly relevant in the services sector where processes, 'products' (i.e. services), and organisational aspects are more closely interrelated than in manufacturing.

Despite these differences, both aspects of innovative experience have in common that resulting dynamics will favour concentration of markets (Dosi, 1988). Both approaches imply that some leading firms can extend their advantages over competitors due to their continuously improving learning capabilities until limiting effects (such as growing organisational inefficiencies) set in. As a consequence, firms will use accumulated experience not only for enhancing the productivity of production and eliminating backward producers but may also try to exploit their market power by charging mark–up prices and by eliminating backward producers. These effects may be particularly important in the case of sequential product innovations where

[4]In an empirical investigation of the dynamic capability model, Knott et al. (2003) conclude that such complementarities may play a major role. Antonelli (2003) provides a theoretical framework of how *complexity* (the generation of knowledge requires the combination of diverse bits of knowledge) and *fungibility* (some specific knowledge can be applied in a variety of different context) can cause increasing returns in the generation of knowledge.

lagging firms and new entrants face severe obstacles in offering substitutes to the leading firms' products. Moreover, to the extent that experience complements ICT as an input of production, falling prices of ICT will exacerbate competitive advantages of firms that have concentrated efforts early on the innovative use of these intermediate goods.

2.3 Specifics of innovation in services

Investments in ICT are most intensive and most dynamic in services (see, e.g., OECD, 2000a). In earlier studies on innovation, the service sector was characterised as a mere applier of technological innovations developed in the manufacturing sector, with ICTs being the most important example. This view has been changing substantially during the last decades.[5] In the following, I limit myself to discuss those aspects that appear particularly relevant for interpreting innovative experience in the context of ICT adoption in services.

In his famous taxonomy of technological activities, Pavitt (1984) classifies services as 'supplier dominated' industries where technological progress is due to technologies developed in manufacturing. Among various critics, Barras (1986; 1990) challenges this view by presenting his theory about a "reverse product cycle" in services as compared to manufacturing. Based on evidence on computerisation in banking, accountancy and local government services, he suggests that technology adoption initiated its own innovation dynamics in services: first, service firms use new technologies mainly for making production and delivery of services more efficient. Only in latter stages, new technologies serve for improving service quality and customisation and for eventually creating new services.

Other researchers point to more elementary aspects of services that make innovation dynamics in services inadequate to compare to manufacturing (e.g., Gallouj and Weinstein, 1997; Sundbo, 2000). Among the most prominent of these characteristics are *intangibility* and *interactive aspects* of services. *Intangibility* relates to the fact that services and the process of their production cannot be separated; services lack an independent physical existence and are not visible. When it comes to innovation, this makes it difficult to distinguish between innovation of products and processes in services.[6] Moreover, the quality of various services (such as consulting or

[5] Tether et al. (2001) and Tether (2003) provide broad discussions and classifications of these theoretical approaches.

[6] Challenging this view, however, Sirilli and Evangelista (1998) and Evangelista (2000) report evidence from Italian innovation surveys indicating that firms in services are well

technical services) is closely linked to the knowledge and skills of people involved in production and the way these competencies are organised (Gallouj and Weinstein, 1997). *Interaction* between providers and consumers of services makes it difficult not only to determine the authorship of an innovation but also to differentiate between mere variations of existing services and original innovations.

Jointly, these peculiarities of services imply that quality and ingenuity of services can not, or at leat not in the first place, be attributed to 'hard' (Tether, 2003), 'tangible' (Gallouj and Weinstein, 1997) or 'embodied' (Evangelista, 1999) technologies, such as equipment, ICT and structures. Instead, 'soft', 'intangible', or 'disembodied' dimensions of technologies involved in the production of services (human skills, legal or financial expertise, organisational and operating practices, etc.) play a pivotal role. Emphasising the role of interaction with clients, Gallouj and Weinstein (1997) and Gallouj (2000) further distinguish intangible aspects of technology into individual *competencies* that are based on individual skills, training, experience and interactions with clients on the one hand, from *systems* of codified or formalised competencies (routines, organisational competencies) on the other.[7] They argue that the interaction with clients is not only by itself a subject and a 'laboratory' of innovations, but also a critical area for the supplier's capacity to absorb and assimilate new competencies. Gallouj (2000) suggests that innovations in services can often be classified as 'ad hoc innovation', 'recombinative innovation', and 'formalisation innovation' or a combination of the categories. These are inherently complex since they are based on knowledge and experience accumulated in the past and presume an understanding of the complex nature of the characteristics of services and the processes to generate them.[8]

Moreover, Gallouj and Weinstein (1997) discuss various types of innovations in their framework and emphasise that intangible dimensions of technology (including individual competencies) are pivotal for innovation in services. They conclude that interactions between the various dimensions of innovations imply that innovational dynamics in services may be determined

able to distinguish between both types of innovation.

[7]Gallouj and Weinstein (1997) illustrate these notions as an analogy to Nelson and Winter's (1982) distinction between 'skills' and 'routines' that has become widely accepted in evolutionary economics.

[8]These views are consistent with results from innovation surveys in Germany (Janz, 2000) as well as the Community Innovation Survey (Tether, 2003) which show that customers and internal sources dominate suppliers as sources for innovation in all services industries.

less by the characteristics and technological trajectories of tangible or hard technologies, such as ICT, but rather by intangible aspects of services technologies (organisation, routines, management methods) as well as cognitive trajectories, such as accumulation of expertise in individual and collective learning processes.

This hypothesis contrasts distinctly with more traditional approaches discussed above that interpret services as a technologically passive and dependent sector. Instead, it complements the considerations of ICT as a GPT from the previous subsections: to the extent that competencies and routines are essential for innovation trajectories in services, firms must complement technological advances embodied in equipment (and ICT in particular) by accumulation of expertise and experience within the firm in order to generate own innovational advances.

A common objection towards the approaches discussed so far concerns the fact that services are too heterogenous to treat them under a 'one–fits–all' theory.[9] Some researchers have tried to overcome this weakness by developing taxonomies and typologies that highlight differences of innovational patterns between service industries (e.g., Evangelista, 2000). However, using both data from the Community Innovation Survey,[10] Tether et al. (2001) and Tether (2003) find that innovation behaviour varies substantially not only between but also within sectors. They suggest that firms face a variety of fields for innovation to engage in — such as introducing cost–reducing processes, offering more flexible and customised services or specialising in particular markets with bespoke services — and that strategic positioning may explain differential innovation behaviour within industries. These considerations relate to the dynamic aspects of innovation and indicate that evolutionary and resource–based approaches apply not only to manufacturing but equally well to service industries. In the empirical part of the paper, these strategic aspects will be taken into account by differentiating between experience resulting from product and process innovations.

Summarising the theoretical considerations so far, the following implications can be highlighted. First, by its general purpose properties, ICT forms a special type of investment good compared to other (non–ICT) types of capital. The productivity effects from ICT use are expected to be deter-

[9]While Barras' (1986) approach has been criticised as being too narrowly tailored to the peculiarities of banking and insurances, approaches that emphasise interactions with clients as a source for innovation (Gallouj and Weinstein, 1997, e.g.) may lack generality due to their focus on knowledge–intensive business services, such as consultants or technical services.

[10]The MIP–S data employed in this paper form the German part of CIS for services.

mined by the firm's ability to complement investments by own innovational efforts (*innovative capabilities*). Second, innovative capabilities are firm–specific and are the result from learning effects from innovations in the past (*innovative experience*). Jointly, these considerations imply that *firms that have innovated in the past can use ICT investments more productively than firms that have not*. Moreover, two overlapping types of innovative experience can be distinguished. (a) If the relevant learning process is localised in ICT, it will be mainly yesterday's ICT–based innovations that increase the productivity of ICT use today. (b) If the organisational capabilities of introducing innovations prevail, experience also from yesterday's innovations in other technological fields are likely to enhance productivity of ICT use today.

2.4 Empirical Model

In order to investigate the hypotheses derived above, a production function framework is used that allows the productivity contributions of the inputs to vary with a firm's innovative experience. A Cobb–Douglas production technology is considered in which the coefficients of the inputs may vary between innovators and other firms:

$$Y_{it} = F(A_{it}, L_{it}, ICT_{it}, K_{it}, J_i) = A_{it} e^{\gamma J_i} L_{it}^{\xi_1(J_i)} ICT_{it}^{\xi_2(J_i)} K_{it}^{\xi_3(J_i)} \tag{1}$$

where Y_{it} denotes the output of firm i in period t, L_{it} is labour input, ICT_{it} and K_{it} represent ICT and non–ICT capital, and A_{it} represents the multi–factor productivity. Innovative experience J_i is assumed to be quasi–fixed in the time span considered in the empirical analysis (which comprises six years) since innovative background cannot be changed easily in the short term.[11]

In the empirical analysis, a firm's innovative experience J_i will be proxied by a dummy variable equalling one for innovative firms. Under this premise, the functional form of $\xi_h(J_i)$ can be expressed as follows without loss of generality:

$$\xi_h(J_i) = \beta_h + \gamma_h J_i, \qquad h = 1, 2, 3, \tag{2}$$

where β_h is the elasticity of input h for firms classified as non–innovators and $\beta_h + \gamma_h$ the elasticity for innovators. Moreover, multi–factor productivity A_{it} is decomposed into a common scale parameter c, a permanent or quasi–fixed component η_i, reflecting firm–specific characteristics that do not vary considerably in the short run (like strategies, management ability, unobserved

[11] The exact definition of the variable J_i for the empirical analysis is discussed in the next section.

intangibles, etc.) and a time–variant part ϵ_{it} that captures short–term shocks like variations in demand, accidents, factor utilisation etc., such that

$$\log(A_{it}) = c + \eta_i + \epsilon_{it}\ . \tag{3}$$

Taking logs on both sides of (1) and inserting (2) and (3) yields:

$$\begin{aligned} y_{it} &= c + \beta_1 l_{it} + \beta_2 ict_{it} + \beta_3 k_{it} \\ &\quad + \gamma J_i + \gamma_1 l_{it} J_i + \gamma_2 ict_{it} J_i + \gamma_3 k_{it} J_i + \eta_i + \epsilon_{it} \end{aligned} \tag{4}$$

with small letters denoting the corresponding logarithmic values.

Thus, the model corresponds to an ICT–extended Cobb–Douglas framework that allows different input coefficients to vary between innovators and non–innovators. In this specification, the coefficients β_h, $h = 1, 2, 3$, represent the elasticities of output with respect to inputs L, ICT and K in non–innovative firms, whereas $\beta_h + \gamma_h$ are the corresponding elasticities in innovative firms. The test for the hypothesis that innovative experience enhances the productivity of input h thus amounts to testing whether γ_h is significantly positive. The direct contributions of innovation J_i to multi–factor productivity, by contrast, are captured by γ.

One implication of (4) is that, for any given share of ICT capital in output ICT/Y, the marginal product of ICT will be higher among innovators. In the simplest (static) case, firms invest in ICT to equate the marginal product of ICT (MPI) to its user costs r.[12] Assuming r to be equal across firms, the optimal ICT stock for all firms is given by the condition $\partial Y_{it}/\partial ICT_{it} = \gamma_2(J_i) \cdot Y_{it}/ICT_{it} = r$. For any given output level Y^*_{it} the optimal level of ICT capital is thus given by $ICT^*_{it} = Y^*_{it}/r \cdot \gamma_2(J_i)$. Similarly, given equal wages w for labour input L, the first–order condition with respect to labour gives $\partial Y^*_{it}/\partial L_{it} = \gamma_1(J_i) \cdot Y^*_{it}/L^*_{it} = w$ such that the optimal endowment of workplaces with ICT capital is:

$$\frac{ICT_{it}}{L_{it}} = \frac{w\gamma_2(J_i)}{r\gamma_1(J_i)} = \frac{w(\beta_2 + \gamma_2 \cdot J_i)}{r(\beta_1 + \gamma_1 \cdot J_i)} \tag{5}$$

This implies that if innovative experience complements ICT but not labour input ($\gamma_2 > 0$ and $\gamma_1 = 0$), the endowment of innovative firms with ICT per employee will be higher than in non–innovative firms. By contrast, analogue considerations for K imply that if innovations do not complement K nor L, non–ICT capital per worker will be uncorrelated to innovations.

A final issue concerns the role of human capital in this framework. Even though innovations may not affect labour input in general, there might be

[12] These user costs are typically defined to consist of depreciation, expected price changes of the capital good, taxes and market interest rate.

a positive effect on the productivity of high–skilled labour. This link is not the main topic of interest of this paper, but its omission may lead to misleading results: if innovations raise the productivity of skilled labour and the share of skilled labour is positively correlated with ICT investment, a positive coefficient β_2 may rather reflect innovation–skill links than higher benefits from ICT in innovative firms. To account for these interferences, the model is slightly extended in the following way. Define N as the total number of workers consisting of low–skilled, medium–skilled and high–skilled employees N_l, N_m and N_h respectively such that $N_{it} = N_{l,it} + N_{m,it} + N_{h,it}$. With $\vartheta_m(J_i)$ and $\vartheta_h(J_i)$ denoting the productivity differentials of medium and highly skilled workers (as compared to the productivity of the low–skilled) conditional on innovation J_i, effective labour is:

$$\begin{aligned} L_{it} &= N_{l,it} + \vartheta_m(J_i) \cdot N_{m,it} + \vartheta_h(J_i) \cdot N_{h,it} \qquad (6) \\ &= N_{it} - N_{m,it} - N_{h,it} + \vartheta_m(J_i) \cdot N_{m,it} + \vartheta_h(J_i) \cdot N_{h,it} \\ &= N_{it} + (\vartheta_m(J_i) - 1) \cdot N_{m,it} + (\vartheta_h(J_i) - 1) \cdot N_{h,it} \\ &= N_{it} + (\vartheta_m(J_i) - 1) \cdot \frac{N_{m,it}}{N_{it}} N_{it} + (\vartheta_h(J_i) - 1) \cdot \frac{N_{h,it}}{N_{it}} N_{it} \\ &= N_{it} \cdot [1 + (\vartheta_m(J_i) - 1) \cdot s_{m,it} + (\vartheta_h(J_i) - 1) \cdot s_{h,it}] \end{aligned}$$

with $s_{m,it} = N_{m,it}/N_{it}$ and $s_{h,it} = N_{h,it}/N_{it}$ denoting the shares of medium– and high–skilled employees in total workforce. Taking logs and with small values for $\vartheta_m(J_i)$, $\vartheta_h(J_i)$, $s_{m,it}$ and $s_{h,it}$, (6) can be approximated by:

$$\begin{aligned} l_{it} = \ln L_{it} &= n_{it} + \ln[1 + (\vartheta_m(J_i) - 1)s_{m,it} + (\vartheta_h(J_i) - 1)s_{h,it}] \qquad (7) \\ &\approx n_{it} + (\vartheta_m(J_i) - 1)s_{m,it} + (\vartheta_h(J_i) - 1)s_{h,it} \end{aligned}$$

with $n_{it} = \ln N_{it}$. Defining $\vartheta_j(J_i) = 1 + \theta_j + \delta_j J_i$ $(j = m, h)$ without loss of generality and substituting for l_{it} in (4) yield:

$$\begin{aligned} y_{it} = \; & c + \beta_1 n_{it} + \beta_2 ict_{it} + \beta_3 k_{it} \qquad (8) \\ & + \gamma J_i + \gamma_1 n_{it} J_i + \gamma_2 ict_{it} J_i + \gamma_3 k_{it} J_i \\ & + \beta_1 \theta_m s_{m,it} + [\gamma_1 \theta_m + (\gamma_1 + \beta_1)\delta_m] J_i s_{m,it} \\ & + \beta_1 \theta_h s_{h,it} + [\gamma_1 \theta_h + (\gamma_1 + \beta_1)\delta_h] J_i s_{h,it} \\ & + \eta_i + \epsilon_{it} \end{aligned}$$

where I make use of the fact that the dummy variable $J_i = J_i^2$. This extension of model (4) with the additional skill variables $s_{m,it}$, $s_{h,it}$ and their interactions with innovation dummy J_i can then be used for assessing the impact of possible interferences of skills.

3 The Data

The model discussed in the previous section is applied to data from the *Mannheim Innovation Panel in Services* (MIP-S) which surveys the innovation behaviour of German firms. It is conducted annually by the Centre for European Economic Research (ZEW) on behalf of the German Federal Ministry for Education and Research and covers a representative sample of more than 2000 firms in German business–related and distribution services.[13] The survey forms part of the Community Innovation Survey (CIS) and its methodology is closely related to the guidelines proposed in the Oslo-Manual on innovation statistics (OECD/Eurostat, 1997). The employed data has an unbalanced panel structure in key variables for the years 1994–99.

For the particular purpose of this paper, the MIP-S data set contains annual data on sales, number of employees in full–time equivalents, skill structure, expenditures on gross investment and on ICT–capital (comprising hardware, software and telecommunication technologies) as well as product and process innovation. I deflate firm sales using consumer prices indices at the two–digit level from the German statistical office. Since the data set does not contain information on intermediate goods, I apprximate firms' value added by multiplying firms' sales with the two–digit industry's average share of value added in gross output based on data from the German statistical office.[14] High– and medium–skilled workers are proxied by the number of employees with university degree[15] and with vocational degree[16]. Due to numerous item non–responses in the skill variables,[17] the resulting 'small sample' containing this information is used mainly to explore the effects from including human capital variables based on equation (8).

Basically, real investment data could be employed to proxy for the corresponding capital stocks. However, this is a very noisy measure of true capital services if time lags (between the time of investment and its productive effects) as well as cyclical fluctuations (that may impact investment demand) are important. To ameliorate this problem, I exploit the longitudinal structure of the data and apply the perpetual inventory method to construct separate stocks for ICT and non–ICT capital based on deflated investment expenditures.[18] For deriving real non–ICT investment, I use deflators from

[13] See Janz et al. (2001).

[14] Both the data set and the transformations using industry–level data are described in more detail in Hempell (2004).

[15] Universities of applied sciences (*Fachhochschulen*) are included in this definition.

[16] This refers to degrees from *Berufs– or Fachschulen* respectively.

[17] Only 591 of the 1222 firms of the sample reported information on the skill structure of their employees.

[18] The details of this proceeding are described in Appendix A and in Hempell (2004) in

the German Statistical office at the two–digit industry level whereas in the case of ICT investment, internationally harmonised deflators provided by Schreyer (2000) are applied.[19]

A final issue is to distinguish between firms with innovative experience and ‘unexperienced’ firms. In each wave of the MIP–S survey, firms are asked whether they have successfully introduced new or significantly improved services or new processes within the last three years. The employed definition of innovation requires an innovation to be new to the firm (not necessarily new to the market) and to be based on technologically new knowledge. It thus includes both original innovators and imitators.

For the analysis, firms that have innovated sufficiently early are regarded as experienced. More specifically, a firm is classified as an ‘experienced innovator’ ($J^{exp} = 1$), if it has introduced a product or process innovation in the first year in which it was observed or in one of the two preceding years. All non–experienced firms are assigned with the value $J^{exp} = 0$. To illustrate this definition, consider two firms A and B, for which data over the period 1994–97 are available. Suppose firm A has reported a product innovation for one of the years 1992–94. It is thus classified as an ‘experienced’ firm ($J^{exp} = 1$). In addition, suppose that firm B, by contrast, has reported no innovation for 1992–1994 (even though it may have reported one for a later period). It is labelled as a ‘not–experienced’ firm ($J^{exp} = 0$). Firm A is considered being ‘experienced’ since for the whole period for which we can observe its inputs and outputs it can rely on experience from earlier innovation.

An alternative definition focusses on the weaker criterion of whether a firm has innovated in *any* of the periods for which data are available. According to this definition, a firm is a — not necessarily experienced — innovator ($J^{inn} = 1$) if it has introduced an innovation during one of the periods (and $J^{inn} = 0$ otherwise).[20] This broader definition is supposed to account for the more general role of innovations, independently of whether these are introduced before or during the period for which productivities are analysed. The comparisons between results based on these two definitions thus highlight

more detail.

[19] German official price statistics on ICT goods tend to understate the real price declines as pointed out by Hoffmann (1998). By contrast, Schreyer (2000) takes this bias into account by calculating harmonised price indices for various OECD countries. He employs official statistics ICT prices in the U.S., which are based on hedonic techniques, as a reference and assumes that the differences between price changes for ICT and non–ICT capital goods are the same across countries.

[20] Suppose the above mentioned firm B has introduced an innovation in 1996. Thus, firm B is denoted as an innovator but not as an experienced one. Firm A, by contrast, satisfies both criterion since being ‘experienced innovator’ implies being an ‘innovator’.

the particular role of innovative experience.

Apart from surveying innovations in general, the MIP–S survey also allows to distinguish between types of innovation, i.e. between the introduction of new or significantly improved services ('product innovation', abbreviated by pd)[21] or of new or significantly improved processes ('process innovations', pc)[22]. As discussed in section 2.3 and corroborated by statistics in Table 8, both types of innovations are closely linked with each other in many cases.[23] Nevertheless, the performance of firms with only one type of innovation may shed light on the question whether strategic positioning in one field of innovation is relevant. The various definitions used in the empirical analysis are summarised in Table (1). The corresponding shares of 'innovators' and 'experienced innovators' by industries and type of innovation are summarised in Tables 8 and 9 in the Appendix.

Finally, firms were asked whether the use of ICT was important for innovative activities (both product and process innovations) during the period 1993–95. The dummy variable J_i^{ICT} is one if a firm answered this question with 'yes'. Interacting J_i^{ICT} with experience variables $J_i^{exp,pd}$ and $J_i^{exp,pc}$ will be used to analyse to what extent firms with innovative experience in the technological proximity of ICT are particularly effective in using ICT. This distinction will be used to assess to what extent innovational learning is localised.

The sample used for the estimation contains only firms with consistent information on at least three consequent periods in order to allow for applying suited panel estimators (see next section). The resulting unbalanced sample consists of 1222 firms with a total of 5107 observations. This corresponds to an average of 4.2 observed periods per firm. Tables 10 and 11 show that the sample reflects industry and size structure of German business–related and distribution services fairly well.[24] The majority of firms in the reference sample are small– and medium–size firms with more than two thirds of the businesses employing less than 100 workers. Tables 6 and 7 report summary statistics and correlations for the logarithmic values of the variables that are

[21] Examples are the introduction of improved after sales services, 24–hour or emergency consultancies, electronic accounting systems etc.

[22] Examples are introducing electronic ordering systems, e–commerce, new security systems etc.

[23] For example, about 72 % of the firms with experience from product innovations have also introduced process innovations (see Table 8)

[24] Exceptions are retail trade, which is substantially undersampled, whereas traffic and postal services as well as software and telecommunication are oversampled. As far as firm size is concerned, large firms are oversampled in their mere number and undersampled in their respective share in sales (see last two columns of Table 11).

Table 1: Definition of alternative classification of innovators

variable	short label	definition*
$J_i^{exp} = 1$	experienced product or process innovator	product or process innovator (or both) in the earliest year observed
$J_i^{exp,pd} = 1$	experienced product innovator	product innovator in the earliest year observed
$J_i^{exp,pc} = 1$	experienced process innovator	process innovator in the earliest year observed
$J_i^{inn} = 1$	product or process innovator	product or process innovator (or both) in at least one of the periods observed
$J_i^{inn,pd} = 1$	product innovator	product innovator in at least one of the periods observed
$J_i^{inn,pc} = 1$	process innovator	process innovator in at least one of the periods observed
$J_i^{ict} = 1$	ICT–based innovator	use of ICT was important to facilitate innovations in period 1993–95

* Note: according to the question design in the underlying questionnaire, a firm is defined to be an innovator in the year Y if it has successfully introduced an innovation in the year Y or some of the two preceding years ($Y - 1$ or $Y - 2$). All firms not fulfilling the corresponding definitions take are assigned the value 0.

employed in the econometric regressions.

Finally, some simple statistics may give some first insights into the challenges for measurement of ICT productivity and the role of innovations. Table 12 reports the (cross–sectional) means and medians of the firms' (longitudinal) averages of capital and output intensity (measured in capital per employee) for the firms in the sample.[25] The figures indicate that in the median firm of the sample, a workplace is equipped with € 1300 of ICT capital, and with about € 25,600 of non–ICT capital highlighting the fact that the share of ICT capital in the total capital stock is very low. Comparing the medians of ICT per worker and conventional capital per worker in Table 12, ICT endowment amounts to 4.8% in total endowment. Similarly, aggregating the firms' time–averages of both types of capital yields a share of ICT capital in total capital of 5% (not reported in the tables). These values correspond very well to the share of 3% calculated by Schreyer (2000) using aggregate data for Germany (including the less ICT–intensive manufacturing sector) in 1996. As argued by Griliches (1994), such small shares of ICT input together with measurement errors may make it difficult to distin-

[25] The corresponding mean values are substantially higher than the median since some firms — in particular of real estate — display very high values for both inputs and output per employee.

guish the output contributions of ICT from stochastic events and may make the identification of productivity effects of ICT resemble the search for the "needle in the haystack". In the econometric analysis, potential biases from measurement errors will therefore be addressed explicitly.

Beyond this, the further columns from Table 12 also shed some light on differences between experienced and other firms with respect to the demand for ICT capital. As pointed out in the discussion of equation 5, the theoretical considerations in the previous section imply that the endowment of workplaces with ICT will be higher among experienced firms. In fact, the mean of the per capita value of ICT stock in experienced firms (defined according to its narrow definition) exceeds the corresponding value of non–experienced firms by a factor of about 1.2. This difference is even more pronounced (factor 2.2) if median values are considered. By contrast, the per capita values of output and conventional capital are substantially higher among non–experienced firms. These simple statistics are consistent with the hypothesis that innovative experience is important for productive investments in ICT but not so much for the use of other types of capital. The next section will investigate to what degree these findings can also be supported by an econometric analysis based on the production function framework developed in the previous section.

4 Empirical Results

In order to estimate the empirical model of equation 4 consistently a system GMM (SYS–GMM) estimator developed by Arellano and Bover (1995) is applied. In this estimation strategy, the GMM estimator in first differences proposed by Arellano and Bond (1991)[26] is extended by the estimation equation in levels instrumented by suitably lagged differences of the explanatory variables. These two specifications are then estimated simultaneously.[27] This estimator controls for unobserved firm effects, measurement errors in the variables and simultaneity of inputs and output which may induce substantial biases in pooled or within OLS regressions (see Hempell, 2004). Moreover, since the variables are highly persistent, the additional moment restriction obtained from the inclusion of the equation in levels substantially

[26] In this strategy, the estimation equation in first differences is instrumented by all the suitably lagged levels of the regressors and estimated by GMM.

[27] The additional moment conditions required for the equation in levels are not very restrictive. As shown by Blundell and Bond (2000), only weak assumptions about the initial distribution of the variables used are necessary. In particular, the joint stationarity of the dependent and the independent variables is a sufficient, yet not necessary condition for the validity of the moment conditions for the equation in levels.

improves the performance of the Arellano–Bond estimator (see Blundell and Bond, 1998a). In order to control for variations in factor utilisation induced by industry–specific business cycles, dummies for 7 industries[28] interacted with years are added to the specification. Finally, a dummy variable for East German firms controls for the productivity differentials due to the transformation process after German unification. For a thorough discussion of the underlying econometric issues, see Hempell (2004).

The corresponding results from applying OLS and the SYS–GMM estimators are reported in Table 2.[29] In the first two columns, the results for the simplest specification of the production function are reported. To illustrate the importance of using appropriate estimation techniques, OLS results are compared to the outcomes from SYS–GMM. The coefficient of ICT is twice as high in the OLS regression, pointing to a substantial bias from omitted fixed effects.[30] In the SYS–GMM specification of column 2, labour and non–ICT inputs are significantly positive, but ICT is only very marginally significant (p–value of 0.106). The output elasticity of labour amounts to two thirds which is consistent with the share of income from labour in the aggregate statistics. The coefficients of ICT and non–ICT capital are 4.9% and 18.9% respectively. The corresponding Sargan–statistic ($p = 0.193$) does not reject the validity of the instruments at the usual significance levels even though the null–hypothesis of no autocorrelation in the errors is rejected at the usual levels.[31]

In the third column of Table 2, the results are reported for the specification as of equation (4) in which all input elasticities are allowed to be different for experienced and non–experienced firms. In these results, the simple coefficients represent the elasticities for unexperienced firms while the

[28] The industry classifications with the corresponding NACE codes are summarised in Table 10 in the Appendix. Since there are no output data available for banking and insurance (only the balance sheet total and insurance premiums respectively), these industries are excluded from the analysis.

[29] All estimations were computed using the DPD98 programme developed by Arellano and Bond (1998) running in GAUSS. For the point estimates, the results from the efficient two–step estimator are reported while the corresponding t–values are obtained from the one–step results. As argued in Blundell and Bond (1998b) on the basis of Monte Carlo simulations, "[i]nference based on one–step GMM estimators appears to be much more reliable when either non–normality or heteroscedasticity is suspected" (142) which may well be the case in the regressions presented here.

[30] See Hempell (2004) for a detailed exploration of the impact of different estimation methods on estimated ICT elasticities in a production function framework.

[31] The tests for first–order and second–order correlation — AR(1) and AR(2) in Table 2 — refer to the specification in first differences. No autocorrelation in the level–equations thus implies negative first–order correlation and no second order correlation.

Table 2: Factors of production and innovational complementarities

	Dep. Variable: log(value added)			
	(1) overall OLS	(2) overall SYS–GMM	(3) inn.: J^{exp} SYS–GMM	(4) inn.: J^{inn} SYS–GMM
log(labour)	0.662***	0.686***	0.601***	0.809***
	(34.779)	(9.681)	(5.112)	(4.581)
log(ICT)	0.091***	0.049	0.019	0.007
	(6.742)	(1.614)	(0.691)	(0.489)
log(non–ICT)	0.208***	0.189***	0.164***	0.182**
	(14.888)	(3.587)	(2.142)	(2.317)
innovation			0.027	0.717
			(0.847)	(1.042)
Interactions of innovation with:				
log(labour)			0.037	-0.164
			(-0.527)	(-0.975)
log(ICT)			0.076**	0.039
			(1.993)	(0.660)
log(non–ICT)			0.031	0.025
			(-0.292)	(-0.103)
R^2	0.840	0.836	0.838	0.834
Wald stat.[df]				
inputs (w/o constants)	510[3]	111[3]	458[6]	629[6]
time and ind. dummies	672[41]	685[41]	750[41]	698[41]
Sargan (p–values)	—	0.193	0.465	0.566
erros (p–values)				
AR(1)	0.000	0.003	0.003	0.003
AR(2)	0.000	0.039	0.056	0.033

***, **, * = significant at the 1, 5 and 10 per cent level respectively
SYS-GMM estimates are obtained from two–step estimation containing a constant, a regional dummy variable for East–German firms as well as interacted industry and year dummy variables. The definition of the variable 'innovator' and the corresponding interactions differs between columns (3) and (4) as as indicated by the subscripts of J^x in the first row (see Table 1, p. 18, and section 3 for definitions). T–values reported in brackets as well as R^2 are obtained from heteroscedasticity–robust first–step results (see Arellano and Bover, 1995, and text). The signs of the coefficients and the corresponding t-values may therefore differ in some cases. The underlying sample consists of an unbalanced panel with 1222 firms and 5107 observations covering the years 1994–1999.

estimates for the interactions (corresponding to coefficients $\gamma_1, \gamma_2, \gamma_3$ in equation 4) thus denote the additional output elasticities for experienced firms

Table 3: ICT and firm–level innovations

	Dep. Variable: log(value added)			
	(1)	(2)	(3)	(4)
	early innovation		some innovation	
	inn.: $J^{exp,pc}$	inn.: $J^{exp,pd}$	inn.: $J^{inn,pc}$	inn.: $J^{inn,pd}$
log(labour)	0.639***	0.652***	0.668***	0.693***
	(9.201)	(9.105)	(9.056)	(9.529)
log(ICT)	0.027	0.010	0.036	0.023
	(1.099)	(0.582)	(1.375)	(1.318)
log(non–ICT)	0.186***	0.189***	0.198***	0.201***
	(3.319)	(3.105)	(3.847)	(4.114)
innovation	0.263	0.196	0.045	0.014
	(1.640)	(1.358)	(-0.212)	(-0.710)
innov.*log(ICT)	0.125**	0.089**	0.019	0.016
	(2.222)	(2.070)	(-0.053)	(-0.456)
R^2	0.837	0.835	0.836	0.836
WALD STAT.[DF]				
inputs (w/o constants)	97[3]	85[3]	81[3]	85[3]
time and ind. dummies	737[41]	722[41]	723[41]	733[41]
Sargan (p–values)	0.199	0.198	0.449	0.200
ERRORS (P–VALUES)				
AR(1)	0.003	0.003	0.003	0.003
AR(2)	0.049	0.052	0.044	0.041

***, **, * = significant at the 1, 5 and 10 per cent level respectively

The definitions of the variable 'innovator' and the corresponding interactions differ between columns as indicated by the subscripts of J^x in the first row (see Table 1, p. 18, and section 3 for definitions). All regressions are estimated by SYS–GMM (see also footnotes to Table 2, p. 21).

compared to non–experienced ones. The hypothesis of innovative experience complementing ICT use predicts the interaction term for ICT to be positive.

The results show that the coefficient of ICT in experienced firms is indeed significantly higher than in unexperienced ones. By contrast, for labour and non–ICT capital, the null–hypothesis of equal elasticities for both types of firms cannot be rejected. These results support the conjecture that innovative experience complements the usage of ICT but not the use of conventional inputs labour and non–ICT capital.

In column 4 of Table 2, the regression with interactions is replicated for the alternative classification of firms J_i^{inn} corresponding to whether they have introduced an innovation in any (not necessarily the first) observed periods. This specification thus abstracts from the role of experience and only considers complementarities between ICT use and innovations independently of the temporal sequence. In this specification, the interaction term for both ICT and non–ICT are positive but fail statistical significance. There is thus no robust evidence pointing to impacts of innovations on the productivity of any particular input of production.[32] Jointly, the results of (3) and (4) indicate that obviously it is only earlier innovations that matter for productive ICT use today. This finding supports the conjecture that innovative *experience* rather than just contemporary innovations help to use ICT productively.

In a more detailed analysis considering different *types* of innovation, Table 3 reports the results for further regressions in which the innovation dummy is interacted only with the ICT input. The first two columns refer to the classification according to the experience (J_i^{exp}) concept while the latter two ones consider innovations at an unspecified point of time (J_i^{inn}). The results confirm the findings of Table 2 showing that also for considering process and product innovations separately, early innovations do have a significant impacts on ICT productivity while innovations in later periods do not. Interestingly, the experience from process innovations seems to matter more in quantitative terms: the elasticity of ICT among firms with experience in process innovations amounts to 0.152 (from 0.027+0.125) as against more modest 0.099 (0.010+0.89) among firms with early product innovations.[33]

Is localisation or technological proximity of experience important for the productivity contributions of ICT? In order to address this question, I rerun specifications (1) and (2) of Table 3 and include the additional interaction of ICT capital with only those experienced firms who attributed high importance of ICT for their early innovations. The coefficient of the interaction $\log(ICT) \cdot J^{exp,*} \cdot J^{ICT}$ thus measures the 'extra' elasticity (i.e. productivity contribution) of ICT in firms with early, ICT–related innovations as compared to experienced firms where ICT had no special importance for innovations. Shortly, this additional term informs about the relevance of experience being localised in ICT.

The results for the relevant ICT variables from this exercise are displayed in Table 4.[34] While for process innovations, the additional term is insignificant, small and negative, it is positive (but also insignificant) in the case of product innovations. However, the additional term impairs the precision also

[32] The not–interacted innovation dummy is substantially higher than in the estimation of col. 3, highlighting a more prominent role of direct productivity contributions of innovations independently of the use of particular inputs. However, in both cases the coefficient of the innovation dummy is estimated imprecisely and fails statistical significance.

[33] This finding of a higher impact of experience from process innovations is corroborated in further unreported regressions in which the dummies for experience from product and from process innovations are interacted with ICT in one regression simultaneously.

[34] The other coefficients and statistics are very similar to the ones of specifications (1) and (2) in Table 3.

Table 4: Technological proximity of experience

Dep. Variable: log(value added)		
	(1)	(2)
innovation type J^*:	process	product
$\log(ICT)$	0.046	0.014
	(1.504)	(0.704)
$\log(ICT) \cdot J^{exp,*}$	0.127	0.061
	(1.152)	(1.118)
$\log(ICT) \cdot J^{exp,*} \cdot J^{ICT}$	-0.010	0.044
	(0.780)	(1.512)
Sargan (p–values)	0.261	0.398
ERRORS (P–VALUES):		
AR(1)	0.004	0.004
AR(2)	0.058	0.064

The dummy variable $J^{exp,*}$ denotes experienced product innovator in the first column and process innovator in the second. J^{ICT} denotes innovators for which ICT was important for innovation in early periods (see Table 1, p. 18, and section 3 for definitions).
The econometric specifications and the sample are the same as in columns (1) and (2) of Table 3 and include the same control variables plus a dummy variable for the interaction $J^{exp} \cdot J^{ICT}$. T–values from one–step estimates reported in brackets (see also notes on Table 3.)

of the other ICT coefficients. These statistically weak results do not allow to draw any strong conclusions. However, they may be interpreted as a sign consistent with theoretical conjectures that localisation is — if at all — relevant mainly for complementarities between ICT use and product innovations.

As pointed out in section 2.4, the above results may be induced by complementarities between ICT and skills if firms with early innovations also employ a high fraction of highly qualified personnel. In order to analyse this potential interference, Table 5 reports results for the skill–augmented model equation (8). Due to numerous item non–responses in the skills variables, however, the underlying sample is substantially smaller with the number of firms dropping from 1222 to 591. In order to illustrate the impacts of this change in the sample, the specification for the simplest Cobb–Douglas case (analogue to the first column of Table 2) is replicated in the first column of Table 5. The most striking change is that the ICT coefficient drops particularly strongly to an insignificant value of 0.015 from 0.049 in the large sample. However, the two coefficients do not differ in any statistically significant way.

The second column of Table 5 reports the results for the Cobb–Douglas specification augmented by the shares of employees with university degree and vocational training. Even though the coefficients of these variables are highly significant (both statistically and economically), the size of the other

Table 5: Innovative experience, skills and the productivity of ICT

	Dep. Variable: log(value added)			
	(1)	(2)	(3)	(4)
log(labour)	0.737***	0.656***	0.723***	0.701***
	(4.379)	(6.518)	(5.518)	(5.412)
log(ICT)	0.015	0.017	0.022	-0.004
	(0.621)	(1.086)	(-0.080)	(-0.333)
log(non–ICT)	0.168	0.208	0.100	0.091
	(1.386)	(1.475)	(0.845)	(0.877)
% university	—	0.827***	0.737**	1.410***
		(3.096)	(2.327)	(2.922)
% vocational	—	0.475***	0.352*	0.688**
		(2.835)	(1.796)	(2.191)
innovation (J_i^{exp})	—	—	0.526***	0.750**
			(1.594)	(2.211)
log(ICT) * J_i^{exp}	—	—	0.177**	0.211***
			(2.062)	(2.738)
% univ. * J_i^{exp}	—	—	-0.510**	-0.794**
			(-2.108)	(-2.481)
% voc. * J_i^{exp}	—	—	-0.093	-0.227
			(-0.660)	(-0.973)
log(ICT) * % univ.	—	—	—	0.083
				(0.246)
R^2	0.825	0.836	0.834	0.830
Wald statistics[df]:				
inputs (w/o constants)	199[3]	486[5]	2957[8]	3913[9]
time and ind. dummies	393[34]	449[34]	513[34]	583[34]
Sargan (p–values)	0.591	0.198	0.044	0.119
errors (p–values):				
AR(1)	0.024	0.029	0.003	0.002
AR(2)	0.146	0.163	0.022	0.028

***, **, * = significant at the 1, 5 and 10 per cent level respectively

All regressions are estimated by SYS–GMM (see also footnotes to Table 2, p. 21). The underlying sample consists of an unbalanced panel with 591 firms and 1887 observations covering the years 1994–1999.

inputs are hardly affected by this extension of the model.[35] This phenomenon may be due to the fact that the skill composition *within* firms changes very little over time, whereas the heterogeneity *between* firms is accounted for also in the former specification by controlling for firm–specific fixed effects.

Controlling for potential interferences of skills on the interaction between ICT and innovative experience, the results from the estimation of the full equation (8) are replicated in column 3 of Table 5. As in the preceding specifications, the interaction between ICT and innovative experience enters

[35] This finding is consistent with similar results reported by Lehr and Lichtenberg (1999).

significantly positive, which points to the robustness of the earlier findings concerning the role of innovative experience. A drawback of the specification underlying col. 3 is, however, that — unlike in the previous specifications — the Sargan test rejects the validity of the instruments at the 5%–level. Moreover, the interaction between ICT and the share of employees with university degree enters significantly negative, implying the somewhat counterintuitive result that the productivity contributions of skills are lower in experienced firms. In order to shed some more light on these results, the estimation equation is extended beyond the regression model of equation (8) in col. (4) by including an interaction between ICT and the share of employees with university degree in addition. This interaction term takes a positive though insignificant value which is consistent with complementarities between ICT and skills found in other studies.[36] However, the qualitative results from col. (3) are broadly corroborated with the interaction terms being even higher in absolute values while the Sargan test does not reject the validity of the instruments used at the 10 % significance level.

Summing up the results so far, there is broad evidence that innovative experience has a significant but asymmetric effect on the productivity of the various factors of production. The impacts are significant only for the use of ICT, with the impact from process innovations being particularly high. The positive effect of successful innovations in the past on ICT productivity is robust to the inclusion of variables controlling for skills and various interactions of these variables with ICT and innovative experience.[37]

One might object against these results that the particular importance of innovations in the past is rather a consequence of technological opportunities than the impact of innovative experience. In particular, some businesses may be more suited than others to improve products or processes by the use of ICT. Those better suited businesses will both be able to reap higher productivity gains from ICT, but are more likely to be early adopters of ICT for restructuring their processes, too. If this is true, the higher productivity potentials found would be spurious. This argument would be a serious objection, indeed, if most of the 'experienced' firms in the sample belonged to the same industries. As can be seen from Table 8 in the appendix, however, the innovator shares do not vary greatly between industries. To illustrate this point in more detail, Table 9 in the appendix summarises the share of experienced process innovators (epc) by industries at the more detailed NACE

[36] See, e.g., Caroli and van Reenen (2001) and Bresnahan et al. (2002).

[37] As set out in section 3, the innovation variables from the employed data include both 'genuine' innovators and imitators. Unfortunately, the data constraints do not allow for a further distinction with respect to these characteristics.

2–digit level.[38] In most of the industries, the share is quite close to the sample average of 61%.[39] This contradicts an eminent importance of technological opportunity as the driving force behind the results.

A related objection may be that the results could be dominated by a higher productivity of ICT use in larger firms. From the innovation literature, it is well known that bigger firms are more likely to innovate (Cohen, 1998). The innovation proxies might therefore rather capture size effects. To address this issue, the robustness of the results has been checked in additional regressions in a translog–production function framework (not reported). Among other features, this more flexible framework explicitly controls for firm–size effects.[40] Also in this specification the ICT coefficient turns out to be significantly higher in experienced firms.[41]

Finally, it may be argued that apart from innovative experience, past innovations may reflect other firm characteristics like management ability and flexibility. Though certainly right, the impact of these underlying factors seems much more likely to impact multi–factor productivity captured by the dummy for innovative experience rather than by the *interaction* of ICT and experience. That is, management characteristics are expected (and partially found) to have a direct impact on overall firm productivity and not so much on the productivity potentials of one of the particular factor inputs.

To sum up, there are three main findings that can be derived from the estimation results. First, innovative experience significantly matters for a productive use of ICT, whereas innovations alone do not exhibit any significant impact. Apparently, the successful implementation of ICT requires a knowledge base in firms which to a large extent depends on firms' innovation behaviour in the past.

Second, experience gathered from past process innovations is quantitatively more substantial than experience from the introduction of new services. On the one hand, this finding is subject to reservations and should not be overstated since it is not possible to apply a sharp distinction between both types of innovation in various cases. On the other hand, the finding is consistent with theoretical arguments as well as with evidence from case studies

[38] The distribution of the innovator shares for the alternative classifications are very similar (not reported).

[39] In 8 of the 13 industries, the corresponding share lies within the range of 51 and 71%.

[40] See Hempell (2004) for further details on this specification.

[41] Moreover, if it was really firm–size that drives the results, the same link between firm size, innovation propensity and ICT elasticity would be expected to hold for innovators in general (including the wider definition as 'panel innovator'). However, for firms that have introduced an innovation in *some* period, the productivity effects of ICT were not found to be higher.

which stress the particular importance of ICT for re–engineering business processes and re–shaping organisational structures within firms.[42] Because of this close link, experience from past process innovations may help reduce the risks of innovation projects and will improve the firm's expectation formation with regard to the costs and benefits of ICT–induced changes.

Third, the positive dependence of ICT productivity on innovative experience is a feature that distinguishes ICT investment from the more conventional inputs non–ICT as well as labour input. Thus, the increasing importance of innovation may well be identified as a key characteristic of the ICT age. Obviously, firms have not been equally prepared for the large range of innovation possibilities induced by the rapid diffusion of ICT. As a consequence, the induced wave of innovation has contributed to a widening of productivity differentials between firms.

5 Conclusions

In this paper, I analyse the productivity effects of ICT use in the German business–related and distribution services with firm–level data. Based on an extended production function framework with labour and two types of capital inputs, I employ a SYS–GMM estimator in order to control for a variety of potential estimation biases, like unobserved heterogeneity, simultaneity of inputs and output and measurement errors. Various impacts and complementarities of ICT investment are identified. First, for a simple Cobb–Douglas specification in which all firms are treated equally, a significant output elasticity of ICT–capital of about 5% is found, indicating substantial productivity effects of ICT in the German service sector in general. Secondly, based on a theoretical model, the production function framework is extended to allow productivity contributions of ICT capital to vary between firms. This more detailed analysis reveals that firms that have introduced process innovations in the past — labelled 'experienced' firms — are especially successful in ICT–use. The output elasticity of ICT in these firms amounts to about 15% and is significantly higher than for non–experienced firms (3%). Third, unlike innovative experience, innovations at some unspecified point of time (accompanying current ICT investments, e.g.) have positive but not statistically significant impacts on ICT productivity. Finally, it is found that the complementary role of innovative experience is a very specific characteristic of ICT since no such complementary link can be observed for investment in

[42] In the service sector, organisational changes are closely linked to the introduction of new or improved processes (see Hipp et al., 2000).

conventional capital. Taken together, these findings support the hypotheses developed in this paper which assign ICT the role of a 'special' capital input: unlike other capital goods, the productive use of ICT is closely linked to innovations in general and the re–engineering of processes in particular. Overall, the results yield broad evidence that innovative experience is a crucial prerequisite for firms to meet the challenges of the 'information economies'.

There are several implications of these findings concerning both theoretical and policy issues. At the theoretical level, the results contribute to a clarification of the role of ICT as a general purpose technology giving rise to complementary innovations. In spite of the diverse uses and the rapid diffusion of ICT throughout all industries, the productivity effects of ICT are far from self–enforcing but rather demand an active implementation strategy within firms. The role of innovative experience found in this paper indicates that the determinants for the efficient use of ICT belong to a firm's long–term strategies rather than being characteristics that can be changed easily in the short term. Innovative experience is likely to be acquired over years rather than within months.

Furthermore, the role of innovative history found at the micro level may also be useful for shedding more light on the differences of ICT–induced productivity effects found between countries. In fact, the competitive and innovative business environment in the U.S. may be one reason that helps explain why the productivity impact of ICT has been much higher there than in continental Europe. The higher innovation pressure in the U.S. over the last decades may have led firms to collect much more diverse innovative experience than more protected firms in Europe. This may have enabled firms in the U.S. to reap higher benefits from the use of ICT. In this respect, ICT may have led to a further widening of the productivity gap both between the U.S. and Europe and between other regional parts of the world economy.

As far as economic policy is concerned, the findings of this paper point to the importance of an innovative business environment that is needed to lay the fundamentals for an efficient use of ICT. New technologies like ICT may be compared to the invention of a new fertiliser in farming: though its potential uses may be fairly general and its costs quite low, a sound climate, a cultivated soil and a gifted farmer will still be needed to actually increase crop yield. Unlike the case of farming, however, the climate in economics may be favoured to a large extent by sound policies. The results of this study suggest that enhancing competition and innovation incentives may serve as an important driver of both the rapid diffusion and a productive use of ICT.

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Appendix

A Construction of ICT and non–ICT capital stocks

For the purpose of the empirical analysis within the production function framework, capital stocks for conventional (non–ICT) capital and ICT capital are constructed separately from investment data applying the perpetual inventory method as follows. Accordingly, the capital stock K_{kt} of type k in period t results from investment $I_{k,t-1}$ in the following way:

$$K_{kt} = (1-\delta_k)K_{k,t-1} + I_{k,t-1} \tag{9}$$

with $k = 1$ for conventional and $k = 2$ for ICT capital and investment.
There are two particular issues to be addressed in this approach. First, reasonable values for the depreciation rates of both types of capital have to be defined. Second, since no information is available on the level of capital stocks, initial capital stocks have to be constructed for all individual firms. Therefore, the method proposed by Hall and Mairesse (1995) for the construction of R&D stocks is applied. Under the assumption that investment expenditures in capital good k have grown at a similar, constant average rate g_k in the past for all firms, equation (9) can be rewritten for period $t = 1$ (1994) by backward substitution in the following way:[43]

$$\begin{aligned} K_{k1} &= I_{k0} + (1-\delta_k)I_{k,-1} + (1-\delta_k)^2 I_{k,-2} + \ldots \\ &= \sum_{s=0}^{\infty} I_{k,-s}(1-\delta_k)^s = I_{k0}\sum_{s=0}^{\infty}\left[\frac{1-\delta_k}{1+g_k}\right]^s \\ &= \frac{I_{k1}}{g_k+\delta_k} \end{aligned} \tag{10}$$

Constant linear depreciation rates are assumed for conventional capital (δ_1) and ICT capital (δ_2) correspondingly. For δ_1, the average depreciation rates by industries at the NACE two–digit level over the years 1991-1999

[43] In fact, the initial value of investment in conventional capital $I_{1,1}$ is replaced by the average of the observed values of conventional investment for each firm. This "smoothing" is aimed at correcting for cyclical effects which might have affected the estimated capital stock due to different initial years in the unbalanced panel. The underlying assumption is that long term growth of investment in conventional capital ($g_1 = 0.05$, see footnote 46) is relatively low compared to cyclical variations in this variable. On the contrary, the first observation on ICT capital was not replaced by the corresponding averages since long-term growth ($g_2 = 0.4$, see main text below) rates of ICT investment are more likely to dominate changes due to cyclical fluctuations.

are employed.[44] For ICT capital, a depreciation rate of 30% is assumed.[45] In particular, by assuming $\delta_1 < \delta_2$ it is taken into account that the fast technological progress in ICT implies more frequent replacement of ICT inventory than of conventional capital (including buildings and office furniture among others). In order to derive the initial capital stocks, assumptions about pre-period growth rates of both types of investments must be made. For non–ICT investment expenditures, an annual growth rate of approximately 5% ($g_1 = 0.05$) is assumed.[46] For ICT investment, no time series are available for Germany. In order to get a rough idea of the evolution of ICT investments during the last decades, U.S. data is used as a rough guideline. Jorgenson and Stiroh (1995) calculate an average annual growth rate of 44.3% in real computer investment and of 20.2% for OCAM (office, computing, and accounting machinery) between 1958 and 1992 for the U.S. Since the share of computers in OCAM has been rising continuously — reaching 94% in 1992 —, an annual pre-period growth rate close to the growth rate of computer investment of $g_2 = 0.4$ is assumed for ICT investment.[47] Since there are time lags between the installation and the productive contribution of capital goods, the capital stocks at each period's *beginning* (or at the end of the corresponding previous period) are taken as measures for both ICT and conventional capital input.

Some 45 firms reported a share of ICT investment in total investment expenditures equal to zero for all the periods surveyed. Since the econometric specification is in logs, these firms, in which ICT can be expected to have low

[44] The depreciation rates by industries are calculated as the shares of capital consumption in net fixed assets evaluated at replacement prices as given by the time series 7719 and 7735 of the German Statistical Office. The resulting depreciation rates hardly vary over time such that averaging over time is of minor importance. The unweighed mean over all service industries amounts to 9% with a maximum in the NACE 72 (data processing) of 21% and a minimum in NACE 70 (real estate) with 2.2%.

[45] Relying on available data from the U.S. indicated by Fraumeni (1997) and Moulton et al. (1999), depreciation rates for IT–hardware, software and telecommunication capital are assumed to be 31.2% for IT–hardware, 55.0% for prepackaged software, 33.0% for custom and own–account software and 15.0% for telecommunication capital. Using data by EITO (2001) for the year 1999, total ICT investment expenditures in Germany consist of 47.0% for IT–hardware, 26.9% for software and 26.1% for end–user and network telecommunication equipment. The weighted mean of depreciation rates — with the market shares as weights — yields an average depreciation rate of ICT capital of $\delta_1 = 0.312 \cdot 0.47 + (0.55 + 0.33)/2 \cdot 0.269 + 0.15 \cdot 0.261 = 0.304$.

[46] Calculations on capital data provided by Müller (1998) show that gross capital stock in German services has grown on average by 4.8% annually between 1980 and 1991.

[47] In fact, later results in the production function estimates turned out to be robust to variations in both g and d.

productivity impacts, would have to be excluded from the sample. However, it seems more likely that ICT investment in these firms is not zero, in fact, but rather very low and rounded to zero by the respondents. In order to prevent potential biases in the results the ICT stock per worker is assumed to be equal to the corresponding industry minimum in these cases and the corresponding values are imputed. Robustness hats show that the qualitative results found in this paper are independent of these imputations.

B Tables

Table 6: Summary statistics

	mean	std.	minimum	maximum
log(value added*)	1.822	1.886	-3.771	10.888
log(employees)	3.899	1.691	0.000	12.647
log(ICT capital*)	-2.446	2.701	-16.003	9.456
log(non–ICT capital*)	0.979	2.641	-6.270	11.679
East German (dummy)	0.422	0.494	0	1

*measured in million €; sample with 5107 observations from 1222 firms

Table 7: Correlations of variables

	log(value added*)	log(emp.)	log(ICT*)	log(non–ICT*)
log(value added*)	1.00			
log(employees)	0.85	1.00		
log(ICT capital*)	0.64	0.62	1.00	
log(non–ICT capital*)	0.67	0.65	0.46	1.00
East German (dummy)	-0.17	-0.08	-0.09	0.04

*measured in million €; sample with 5107 observations from 1222 firms

Table 8: Share of innovators by industries

industry	J^{exp}	J^{inn}	$J^{inn,pc}$	$J^{inn,pd}$	$J^{exp,pc}$	$J^{exp,pd}$	$J^{exp,pc}$ & $J^{exp,pd}$
wholesale trade	55.8	78.5	64.5	75.6	37.2	52.3	33.7
retail trade	53.7	74.7	63.2	70.0	37.9	47.9	32.1
transport and postal services	59.9	80.6	69.8	78.4	50.0	55.0	45.0
electronic data processing and telecom.	81.0	97.0	90.0	97.0	60.0	78.0	57.0
consultancies	68.0	88.3	82.5	83.5	54.4	62.1	48.5
technical services	72.7	91.6	84.6	84.6	58.7	61.5	47.6
other business–related services	54.5	76.7	67.1	75.3	37.0	49.7	32.2
all industries	61.0	81.8	71.9	78.6	45.4	55.5	39.9

All values are percentages of firms that take the value one for the corresponding innovation variable J. For the underlying definitions, see section 3 and Table 1, p. 18.

Table 9: Share of firms with innovative experience*, by industries

industry**	50	51	52	60	61	63	64	70	71	72	73	74	90
share of innovative firms (%)***	46.5	55.8	58.0	54.5	66.7	63.6	66.7	47.0	42.1	81.1	70.6	66.2	60.9
# firms in sample	71	172	119	88	6	121	12	83	19	95	17	355	64

* see definition of J^{exp} in Table 1, p. 18.
** defined at NACE 2-digit level.
*** shares of firms that are experienced innovators ($J^{exp} = 1$).

Table 10: Comparison of sample and population by industries

		sample		population*
industry	NACE–digit	# firms	share (%)	share (%)
wholesale trade	51	172	14.1	10.6
retail trade	50, 52	190	15.6	31.3
transport and postal services	60–63, 64.1	222	18.2	11.7
electronic processing and telecom.	72, 62.2	100	8.2	3.4
consultancies	74.1, 74.4	103	8.4	12.1
technical services	73, 74.2, 74.3	152	11.7	10.7
other business–related services	70, 71, 74.5-.8, 90	292	23.9	20.3
all industries		1222	100	100

*German service firms with 5 and more employees in 1999.
Source: German Statistical Office, ZEW and own calculations

Table 11: Comparison of sample and population by size classes

size class (# employees)	full sample # firms	full sample firms (%)	population* firms (%)	population* sales (%)
5–9	205	16.8	57.6	9.4
10–19	206	16.9	24.0	9.9
20–49	254	20.8	11.7	9.7
50–99	156	12.8	3.5	6.9
100–199	168	13.8	1.6	6.0
200–499	102	8.3	1.0	7.0
500 and more	131	10.7	0.6	51.1
all size classes	1222	100	100	100

*German service firms with 5 and more employees in 1999.
Source: German Statistical Office, ZEW and own calculations

Table 12: Capital intensity and labour productivity by innovative experience

	all firms mean	all firms median	experienced firms mean	experienced firms median	others mean	others median
ICT per worker	3,801	1,302	4,094	1,705	3,343	790
non-ICT per worker	226,947	25,574	182,428	22,758	296,481	29,432
value added per worker	122,198	60,575	114,497	57,870	134,225	65,632
# firms	1222		667		555	

Values in € in prices of 1996. "Experienced firms" refers to firms that have successfully introduced a process or a product innovation in the first observed year or one of the two preceding years (J_i^{exp}, see Table 1, p. 18). The figures are calculated as the means and medians of the unweighed firms' means over time, based on the full sample of 1222 firms.